
Person Identification Based on Hand Tremor Characteristics

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Abstract

A plethora of biometric measures have been proposed in the past. In this paper we introduce a new potential biometric measure: the human tremor. We present a new method for identifying the user of a handheld device using characteristics of the hand tremor measured with a smartphone built-in inertial sensors (accelerometers and gyroscopes). The main challenge of the proposed method is related to the fact that human normal tremor is very subtle while we aim to address real-life scenarios. To properly address the issue, we have relied on weighted Fourier linear combiner for retrieving only the tremor data from the hand movement and random forest for actual recognition. We have evaluated our method on a database with 10 000 samples from 17 persons reaching an accuracy of 76%.

access to buildings - are accessed only by a legitimate user and by nobody else. By using biometric recognition, a system can identify a person based on “who she/he is” rather than “what she/he has” (card, token, key) or “what she/he knows” (password, PIN). While biometric systems may get extremely accurate even for large scale identification applications (as for instance the US-VISIT program based on fingerprint recognition) usually the performance comes with the cost of intrusive evaluation which leads to a low acceptability from people.

In the recent years we note the expanding use of smartphones in our daily life. In 2013, smartphones sales have surpassed in U.S. the basic mobile phones (Ipsos Media CT, 2013) and in 2015 have become the most employed Internet access device (Bosomworth, 2015). Smartphones, if left unsecured, can grant access to the user’s private information: email correspondence, address book, any unsecured documents and potentially banking accounts. Lock screens have been proven inefficient for a user that is concerned with security and some smartphone models include fingerprint readers.

In this paper we would like to point the attention of the reader to the human involuntary hand tremor as a new biometric measure. Furthermore, as currently most smartphones are delivered with inertial sensors capable of measuring it, its applicability is immediate and we will show that the reachable discrimination power is at least sufficient for low-security scenarios.

Tremor is a behavioral biometric falling in the same category as gait (Little & Boyd, 1998), (Nixon &

1. Introduction

Biometric recognition refers to an automatic identification of individuals using metrics derived from their physiological and/or behavioral characteristics (Jain et al., 2000). The purpose of such a system is to ensure that sensitive applications, such as computer systems security, mobile phones, credit cards, secure

to be submitted in

Carter, 2006): while for limited amounts of time it is reliable, it may not remain invariant especially over a long period of time, due to major injuries involving hand joints, certain medications, inebriety, muscle tiredness or weakness, normal aging, stress, anxiety or fatigue (Andrade et al., 2013). As recent studies (Veluvolu & Ang, 2011) have shown that tremor can be efficiently distinguished from voluntary movement, our idea is to use tremor based features to identify the person that holds the smartphone.

We propose a new biometric system based on involuntary tremor detection using inertial sensors (accelerometer and gyroscope) that are already integrated into smartphones. This system can be used for low security applications like automatically unlocking the smartphone only if it is held by the recognized owner. While the here presented study shows high discrimination power over a limited number of persons, we cannot be sure that tremor fingerprint is unique amongst millions of persons.

The remainder of the paper is constructed as follows: in Section 2 we discuss relevant prior work, in section 3 we present the proposed methodology, while in section 4 to discuss the achieved results. Section 5 is dedicated to conclusions and discussions.

2. Related Work

Hand Tremor Studies. The human tremor is defined as “a rhythmic and involuntary oscillation of a body part, caused by reciprocal innervations of a muscle, which leads to repetitive contractions” (Mansur et al., 2007). The human tremor can be categorized in two main classes: resting tremor (which can be noticed when the muscles are not contracted) and action tremor (Andrade et al., 2013). The action tremor manifests during a voluntary muscle contraction. The action tremor encompasses postural, kinetic, intentional, task-specific and isometric tremor and is the type of tremor that is the most likely to appear when using a smartphone. Another classification of the tremor types takes into account its nature (Mansur et al., 2007): physiological tremor (which is present in all healthy people) and pathological tremor (associated with various diseases or conditions such as Parkinson disease). Multiple studies summarized by Mansur et al. (Mansur et al., 2007) concluded that physiological tremor has most of the energy in the [7-12] Hz domain while pathological one has many components in lower ranges. In the current study we have only included persons known not to be suffering from any tremor-related conditions.

As all humans exhibit a form of tremor, its study has received sufficient attention. Tremor compensation is important in microsurgical applications (Veluvolu & Ang, 2011) where involuntary movements needed to be counteracted. The majority of the existing techniques rely on low-pass filtering approaches which are successful in compensating tremor, but the inherent time delay is a major drawback. To overcome this problem, adaptive filtering approaches have been developed and are well-suited for tremor estimation as they can adapt to the changes both in frequency and in amplitude of the tremor signal. Fourier Linear Combiner (FLC) (Vaz et al., 1994) is an adaptive filter that operates by adaptively estimating the Fourier coefficients of the known frequency model according to the least mean square (LMS) optimization algorithm. Weighted frequency Fourier Linear Combiner (WFLC) is an adaptive algorithm which models any quasi-periodic signal as a modulating sinusoid and tracks its frequency, amplitude and phase which means it incorporates the frequency adaptation procedure into FLC and can be successfully used for adaptive tremor cancellation (Riviere et al., 1998).

Another aspect of major interest was the automatic recognition of one of the tremor categories. The most popular division is between physiological tremor, essential tremor and parkinsonian tremor. High separation rates are reported by (Jakubowski et al., 2002), which relies on a multi-layer perceptron classification of features derived from high order statistics, or by (Soran et al., 2012) which feeded the filter output in a Support Vector Machine (SVM).

In parallel, due to their inclusion in smartphones, a multitude of applications are based on inertial sensors. For instance, let us refer to the work of Sindelar and Sroubek (2013) which aimed to remove the camera shake without hardware stabilization or to (Siirtola & Rönning, 2012) which has aimed at user activity recognition.

Biometric Measures. Currently a multitude of biometric measures were proposed and evaluated in previous academic works. In the seminal review on the topic, Jain et al. (2004) discussed the following measures: DNA, ear (shape and structure of the cartilaginous tissue), face, facial, hand and hand vein infrared thermograms, fingerprint, gait, hand and finger geometry, iris, keystroke, odor, palmprint, retinal scan, signature and voice. In a more recent review of biometric measures, Unar et al. (2014) have added finger knuckle print, tongue print and also point to the so called soft biometrics (i.e “characteristics that lack distinctiveness and permanence because they are most

common among humans”).

The use of a hand tremor as a biometric measure, to our best knowledge was not discussed previously in the academic literature, but only named in the intellectual property domain (Liberty et al., 2007). Regarding this work we must point out that, due to the specificity of the publication domain, it does not report any actual results and only discuss general approachable designs, out of which in the preferred implementation also includes a laser pointer for identifying the user that holds a remote control or a mouse.

Thus we argue that the work proposed here, as it details not only the idea but also the system used for implementation and reports results that are obtained in real life scenarios, opens the path for a new direction of research with great potential.

3. Methodology

The proposed hand tremor analysis system (shown in Figure 1) contains the first three typical (Jain et al., 2004), (Unar et al., 2014) modules of a biometric system.

The first module regards data collecting from the inertial sensors which are built-in the mobile phone.

The second stage includes two steps: complex movement filtering to extract the tremor data and the actual feature extractor that is used to obtain the attributes employed for tremor classification.

Finally, in the matcher module, which in fact is a decision making module, the identity of the presumed user is established. The actual implementation relies on a Random Forest classifier.

The sensors’ data acquisition and the prefiltering method are discussed in sections 3.1 and 3.2. The feature extraction process is explained in section 3.3 and the classification is discussed in section 3.4.

3.1. Sensors

Our tests were focused on smartphones available on the market and on the inertial sensors delivered implicitly: 3-axes gyroscopes and accelerometers. Each of the three spatial axis (X,Y,Z) movement is recorded by an accelerometer (which measures translational acceleration) and by a gyroscope (which measure rotational velocity).

For actual recording, we have developed an application that records the gyroscope and accelerometer data at a sample rate of 100 Hz. While this was the best choice provided by the API we have used we point that any

higher frequency, while it comes with cost of more resources, may be beneficial for system accuracy.

To eliminate unwanted movements from the beginning and end of each recording session we have removed the first and last 100 milliseconds, which may be affected by the phone state transition. We divide each signal axis recording into one second windows. The data from one window will form a sample from our data set.

3.2. Prefiltering

To remove the signal noise we rely on the WFLC algorithm for filtering. As previously mentioned, the WFLC is an adaptive filter that can adapt to a quasi-periodic signal of an unknown frequency, amplitude and phase. The WFLC algorithm is an extension of the standard FLC algorithm that showed to lead to superior performance when faced with a signal that displays an oscillatory pattern but with a time-varying period as WFLC may estimate the signal value at non-fixed frequencies (Riviere et al., 1998). In the next paragraphs we will recall the WFLC algorithm main steps.

The input of the WFLC is the inertial sensor signal (s_k) as measured at the sampling moment k . The adaptive vector w_k estimates the signal amplitude and phase and ω_{0_k} , the frequency of the signal. Depending on the instantaneous difference, ϵ_k , WFLC adjusts, at each iteration, ω_{0_k} and w_k . The problem is a typical convex optimization one and it is solved by the adjustment of the standard least mean square (LMS) algorithm.

The state vector $x_k = [x_{1_k} \dots x_{2M_k}]^T$ used by the WFLC algorithm is composed of the sine and cosine functions computed using the frequency weight w_{0_k} and M is the order of the Fourier series representing the measured signal s . μ_0 , μ , μ_b are the frequency, amplitude and bias adaptation gains, respectively.

$$x_{rk} = \begin{cases} \sin\left(r \sum_{t=0}^k \omega_{0_t}\right) & 1 \leq r \leq M \\ \cos\left((r-M) \sum_{t=0}^k \omega_{0_t}\right) & M+1 \leq r \leq 2M \end{cases} \quad (1)$$

The update is:

$$\epsilon_k = s_k - w_k^T x_k + \omega_{b_k} \quad (2)$$

ω_{b_k} is introduced in the computation of ϵ_k to estimate and remove the bias present in the signal (Veluvolu & Ang, 2011), due to possible low frequency components

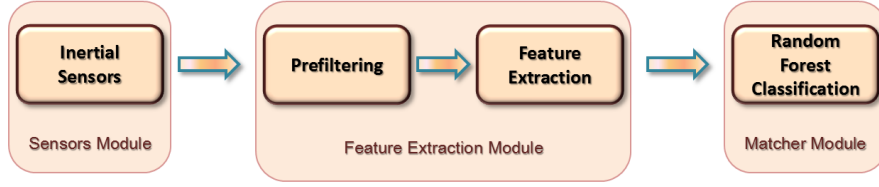


Figure 1. The stages of the proposed hand tremor analysis system.

and/or drift.

The initialization is:

$$\omega_{0_{k+1}} = \omega_{0_k} + 2\mu_0\epsilon_k \sum_{r=1}^M r(w_r x_{M+r} - w_{M+r} x_r) \quad (3)$$

while the unknown frequency and adaptive weight updates are:

$$w_{k+1} = w_k + 2\mu x_k \epsilon_k \quad (4)$$

$$\omega_{b_{k+1}} = \omega_{b_k} + 2\mu_b \epsilon_k \quad (5)$$

The order of the Fourier series M used for representing the measured signal s , was set to $M = 5$. We have found that $\mu_0 = 10^{-5}$, $\mu = 0.3$, $\mu_b = 2.5 \cdot 10^{-8}$ and $w_0 = 2$ produced the best estimate for the voluntary movement.

As the accelerometers and gyroscopes have three axes X , Y and Z , we filter using WFLC each of the axes of accelerometer and gyroscope data.

We then compute the acceleration magnitude as:

$$A_{norm} = \sqrt{A_x^2 + A_y^2 + A_z^2} \quad (6)$$

The gyroscope magnitude is computed similarly and is used for the tremor features extraction.

3.3. Feature extraction

Following the previous works on classifying the tremor into physiological categories we note that the main characteristics are related to favored frequencies (Mansur et al., 2007), (Andrade et al., 2013). Thus, the extracted features are focused on spectral description of the acquired signals.

For the actual implementation we relied on LibXtract (Bullock & Conservatoire, 2007) and extracted 12 features in both time and frequency domains (listed Ta-

Table 1. List of Time Domain Features. Vector \mathbf{x} is the time domain representation of data. N is the number of elements in \mathbf{x} .

Feature Name	Description
Mean	$\bar{x} = \frac{1}{N} \sum_{i=1}^N x(i)$
Standard Deviation	$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x(i) - \bar{x})^2}$
Average deviation	$D_x = \frac{1}{N} \sum_{i=1}^N x(i) - \bar{x} $
RMS Amplitude	$A = \sqrt{\frac{1}{N} \sum_{i=1}^N (x(i))^2}$
Highest Value	$H = (\max x(i) _{i=1 \dots N})$

bles 1 and 2) for each of the gyroscope and accelerometer axis and magnitude.

Also, as tremor is a quasi-periodic movement, we have considered that the spectral density estimation can produce more information on the rhythmic movement. Spectral density characterizes the frequency content of a signal and detects any periodicities in the data, by observing peaks at the frequencies corresponding to these periodicities. The simplest technique to estimate the spectrum is the periodogram, given by the modulus squared of the discrete Fourier transform (Stoica & Moses, 2005). We have extracted for the periodogram (i.e. discrete approximation of the power spectral density) some of the features that we have used for the frequency domain and added the top three frequencies, which define the tremor as showed in Table 3.

Overall it resulted in $(3 \text{ axis} + \text{magnitude}) \times (2 \text{ sensors}) \times (22 \text{ features}) = 176$ features for each sample.

3.4. Matcher Module

In the current evaluation we have focused our attention on an identification scenario: the system aims to recognize the individual by searching the templates of

Table 2. List of Frequency Domain Features. Vector \mathbf{y} is the frequency representation of data. Vectors \mathbf{y}_m and \mathbf{y}_f hold the magnitude coefficients and bin frequencies respectively. N is the number of elements in \mathbf{y}_m and \mathbf{y}_f .

Feature Name	Description
Spectral Standard Deviation	$\sigma_s = \sqrt{\left(\sum_{i=1}^N (y_f(i))^2 y_m(i) \right) / \left(\sum_{i=1}^N y_m(i) \right)}$
Spectral centroid	$C_s = \left(\sum_{i=1}^N y_f(i) y_m(i) \right) / \left(\sum_{i=1}^N y_m(i) \right)$
Spectral skewness	$\gamma_s = \left(\sum_{i=1}^N (y_m(i) - C_s)^3 \right) / \sigma_s^3$
Spectral Kurtosis	$\beta_s = \left(\sum_{i=1}^N (y_m(i) - C_s)^4 \right) / \sigma_s^4 - 3$
Spectral Crest	$CR_s = (\max y_m(i) _{i=1 \text{ to } N}) / C_s$
Irregularity-K	$IK_s = \sum_{i=1}^{N-1} \left y_m(i) - \frac{y_m(i-1) + y_m(i) + y_m(i+1)}{3} \right $
Irregularity-J	$IJ_s = \frac{\sum_{i=1}^{N-1} (y_m(i) - y_m(i+1))^2}{\sum_{i=1}^{N-1} (y_m(i))^2}$

all the users in the database for a match. From a classification point of view, the system should be trained and tested over categorical variables; thus a machine learning step is deemed.

While in the later period the deep networks (LeCun et al., 2015) seem to provide the best accuracy, yet they need large training sets and even with latest progress (Ba & Caruana, 2014) they still require significant resources while testing. From the rest of classifiers, following the large scale study by (Fernández-Delgado et al., 2014) indicates the family of aggregated decision trees as the best performing. This family also has the advantage of having a good generalization error while testing and being robust to various stresses.

As we will further show in the next section the best result was achieved with a Random Forest Classifier (Breiman, 2001).

4. Implementation and Results

4.1. Databases

As no public database is available for a tremor based person recognition purpose, we have collected our own dataset. For this purpose two smartphones, a Nexus 6 and a HTC One M9, both running Android 5.0 Lol-

Table 3. List of Power Spectral Density Features. Vector \mathbf{p} represents the periodogram of the data. Vectors \mathbf{p}_m and \mathbf{p}_f hold the magnitude coefficients and bin frequencies, N is the number of elements in \mathbf{p}_m and \mathbf{p}_f .

Feature Name	Description
Periodogram Standard Deviation	$\sigma_p = \sqrt{\left(\sum_{i=1}^N (p_f(i))^2 p_m(i) \right) / \left(\sum_{i=1}^N p_m(i) \right)}$
Periodogram centroid	$C_p = \left(\sum_{i=1}^N (p_f(i)) p_m(i) \right) / \left(\sum_{i=1}^N p_m(i) \right)$
Periodogram skewness	$\gamma_p = \left(\sum_{i=1}^N (p_m(i) - C_p)^3 \right) / \sigma_p^3$
Periodogram Kurtosis	$\beta_p = \left(\sum_{i=1}^N (p_m(i) - C_p)^4 \right) / \sigma_p^4 - 3$
Periodogram Crest	$CR_p = (\max p_m(i) _{i=1 \text{ to } N}) / C_s$
Periodogram Irregularity-K	$IK_p = \sum_{i=1}^{N-1} \left p_m(i) - \frac{p_m(i-1) + p_m(i) + p_m(i+1)}{3} \right $
Periodogram Irregularity-J	$IJ_p = \frac{\sum_{i=1}^{N-1} (p_m(i) - p_m(i+1))^2}{\sum_{i=1}^{N-1} (p_m(i))^2}$
Top three peri-odogram frequencies	$[H_1; H_2; H_3] = [(\max p_m(i) _{i=1 \dots N_1}), (\max p_m(i) _{i=N_1 \dots N_2}), (\max p_m(i) _{i=N_2 \dots N})]$

lipop operating system, were used to construct two separate databases. The application recorded the gyroscope and accelerometer data at a sample rate of 100 Hz. As the Nexus database is larger (10 000 samples vs. 2150 samples), the discussed results will be based on this database.

For the data collection, our goal was to collect the tremor data while the participants were actively using the smartphone. During the data collection, most persons were using the developed application for embedded camera. Some took pictures, others recorded videos, most people walked while using the application. We have considered the possibility that the tremor fingerprints can be different if the person is holding the smartphone with both hands or just one hand, so we have asked the participants to vary their grip.

The training and the test data was gathered from 17 people. The data from a single person was acquired in multiple sessions distributed among several weeks. For a person the recording session took place at various moments of the day, to include examples where he is

more relaxed or more tired. The target group consisted of 9 males and 8 females in the [20-60] years range age.

4.2. Training and Testing

Data collected from all the subjects was pooled together. The train and test data was randomly drawn from this pool, ensuring no overlap between the train and test sets. We used this approach as it is a good estimator for the generalized performance of the different classifiers.

Furthermore, to test in real-life condition, we ensure that in fact, for a single person, the *samples* used for training and respectively for testing were acquired in *different days*.

Accuracy measures. In a biometric system, there are two types of errors (Jain et al., 2004): (1) mistaking biometric measurements from two different persons to be from the same person (called *false match*) and (2) mistaking two biometric measurements from the same person to be from two different persons (called *false nonmatch*). Also, the system performance at all the operating points (thresholds) can be depicted in the form of *accuracy* which is the proportion of true results (both true matches and true non-matches) amongst the total number of cases examined (Metz, 1978).

4.3. Parameter Choice

Classifier. The family of decision trees contains multiple choice for classifiers. The most popular are random forest and bagged ensemble of trees. To determine which choice yields the best performance, we comparatively evaluated random forest, bagged ensemble and from other categories, the K-nearest neighbour (KNN) based on Euclidean distance ($K = 7$) and Support vector Machine based on Sequential Minimal Optimization (SMO) learning algorithm. For the actual implementation we relied on WEKA machine learning toolkit (Hall et al., 2009). We have used 25% of the database for testing and we have assured that the data was recorded on different days. Results are presented in Table 4. As one may see, the Random Forest lead to best results. Further experimentation rely on the Random Forest.

Number of trees. We have experimented with one to 200 trees that were fully grown with 80% of the attributes used in random selection. Ensembles tend to “overtrain”, meaning they produce overly optimistic estimates of their predictive power, so we have tested how the number of trees influences the classifier’s accuracy on an independent test set (Figure 2). One may

Table 4. Average accuracy, false match rate and false non-match rate for the classification algorithms tested with the full feature set with a one-second sliding window.

Classifier	Accuracy for the test data	False Match Rate	False Non-Match Rate
Bagged Trees	0.70	0.026	0.26
Random Forest	0.76	0.03	0.24
SMO	0.365	0.079	0.63
KNN	0.545	0.036	0.49

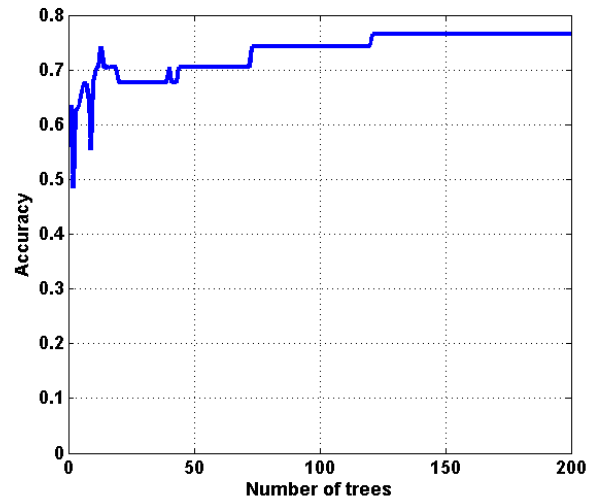


Figure 2. The classification accuracy increases with the tree number for the test data.

note that after 130 trees, the classification accuracy does not vary.

Window size. To determine the optimal sample length we experimented with different windows time sizes, from 0.5 to 5 seconds. The results showed in Table 5 indicate that the one-second window has the best results, while the acquisition time is short enough not to be perceived by the user.

Contrary to the standard disjoint windows we have also tried overlapping windows to various percentages. Yet in all cases the accuracy decreased when compared to preferred choice.

4.4. Experiments

Frequency Domain. For the first experiment we aim to validate prior work conclusions regarding relevant frequency domain for physiological tremor. Thus

Table 5. Average accuracy for the tested window sizes with the random classifier and 100 trees.

Window size (sec)	Average Accuracy	Average accuracy 50% overlap
0.5	0.477	0.506
1	0.761	0.684
1.5	0.623	0.581
2	0.609	0.524
3	0.559	0.458
5	0.534	0.512

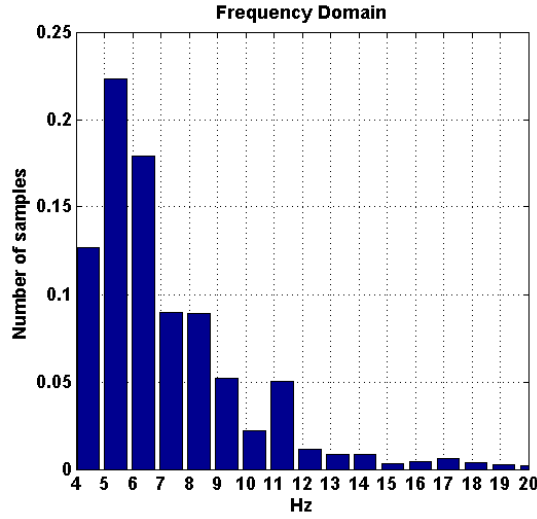


Figure 3. Frequency domain for the filtered hand tremor.

we computed and presented in Figure 3 the normalized power spectral density (i.e. frequency histogram). According to our experiments 72% of the tremor is contained by the to 4-7 Hz range, while 24% corresponded to 7-10 Hz and 45% to 6-10 Hz.

The found results are in concordance with previous work (Andrade et al., 2013), which concluded that the bandwidth of the resting tremor is 4-7 Hz, as the bandwidth for the kinetic tremor is 7-15 Hz.

Feature ranking. The tree ensemble classifier contains implicitly a feature ranking tool. If one counts the number of splits based on a particular feature he will find the overall ranking. For the proposed problem the most relevant features are presented in Table 6.

Performance across persons. Under the assumption that some individuals may have more similar fea-

Table 6. Feature Ranking - the most relevant 5 features.

Rank	Feature	Dataset
1	Irregularity J Periodogram	Accelerometer Magnitude
2	Irregularity K Periodogram	Accelerometer Z Axis
3	Irregularity J Periodogram	Gyroscope Z Axis
4	Irregularity K Periodogram	Accelerometer Magnitude
5	Irregularity K Periodogram	Gyroscope Y Axis

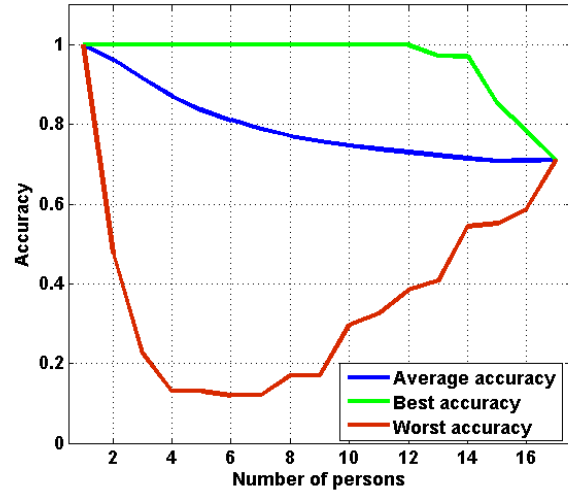


Figure 4. Minimum, mean and maximum accuracy when the person number varies.

tures than others, we have trained and tested all the possible combinations of two to seventeen classes (i.e. persons). The results are showed in Figure 4. One should notice while the average performance is always above 76%, there are some classes that can be very similar (i.e. person cannot be discriminated using the basic setup). Yet these results are obtained using the same set of features. When we focused on the group of 4 that contained the “similar” persons, and we searched for a different feature selection, the performance increased to over 60%. Concluding, the discrimination is still possible, but one needs to build a more powerful feature selection/machine learning system.

Different smartphones. We have tried to determine if a person can be tracked using two smartphones. In order to test this situation and determine if this biometric can become a privacy issue, we

have recorded samples with both smartphones consecutively (i.e. database cross-validation). We have used the classifier trained with the data gathered with the Nexus to classify the samples recorded with the HTC and the average accuracy was 45% significantly lower than 76% achieved only on the Nexus database. The performance evaluated only on the HTC, due to the fact that we were using a smaller database, is even better (88%).

Based on these findings, we conclude that the classifier (and the learned module) is currently not transferable from one smartphone to another. This may be explained based on the following findings: (1) the most important features, as presented in Table 6, are computed on the accelerometer signal; (2) past work on device fingerprinting (Bojinov et al., 2014) shows that accelerometers have a unique noise fingerprint. Thus the specificity of accelerometer noise is incorporated with the learned model and currently it forces us to train the classifier independently on each smartphone.

Tremor may not remain invariant over a long period of time, due to major injuries involving hand joints, certain medications, inebriety, muscle tiredness or weakness, normal aging, stress, anxiety or fatigue. It may not be very distinctive, but it is sufficiently discriminatory for low-security applications, like smartphone unlocking. This technique is very simple, relatively easy to use and inexpensive, because it doesn't require additional sensors.

Verification. We also tested the capabilities of the tremor system to work in the verification mode. In this mode the system should validate a person's identity by comparing the captured data with her own stored template. Given the Nexus database of 17 persons with the training scheme as discussed, we have run on each testing sample and we have achieved 98% accuracy.

5. Discussion

In this section we will review some of the found results and discuss some of the implications in the background of general biometric measures.

5.1. Does the tremor qualify as a biometric measure?

Jain et al. (Jain et al., 2004) notes that "Any human physiological and/or behavioral characteristic can be used as a biometric characteristic as long as it satisfies the following requirements": *universality*, *distinctiveness*, *permanence*, *collectability*. Additionally,

same the authors observe that *performance*, *acceptability* and *circumvention* should be considered when discussing any biometric measure.

Universality. Previous works on the tremor (Mansur et al., 2007) (Andrade et al., 2013) concluded that it is present in all persons. The main difference among different people is that certain ill persons exhibit an augmented form of tremor (e.g. pathological tremor) characterized by lower dominant frequency and increased amplitude. The finest form of tremor is encountered in individuals that actively practice its reduction, such as microsurgeons; yet even here its amplitude does not go below the aimed 10 μm (Charles, 1996) needed for most precise surgical operations.

Distinctiveness and performance. This is the most obvious criteria when ranking various biometric measures. The here computed performance is 76% for different persons with a low for a specific group of 4. In the worst case only after we used a dedicated feature selection we got a 60% separation. Yet testing the capabilities of tremor as biometric measure is only at its initial attempt and we are confident that dramatic increase of performance is achievable. To actually find the measure limits, much larger databases (with more persons, different inertial sensors, many realistic stresses) are needed.

However, it is also against intuition to believe that tremor may actively compete against biometrics such as DNA or fingerprint in terms of accuracy. It is more likely that its distinctiveness may outperform that of the gait and compete with written signature, thus falling into the "low - medium" range.

Permanence. Our tests showed that tremor characteristics are invariant over a period of several weeks. Based on intuition one may argue that time invariance should span significantly larger periods such as months to years. However aging and certain medical conditions (arm issues, blood tensions, neurological diseases) will definitely affect it and limit its time invariance.

Collectability. In this work we have used a smartphone that include inertial sensors to acquire tremor data and rather simple and low-cost features to actively describe it. Furthermore, to measure this biometric of one person he/she simply should hold in hand an device integrating inertial sensors and recording means (analog-to-digital converter, processor, memory); the hardware requirements are obviously easy to

meet. In conclusion, we consider that tremor is highly collectible.

Acceptability. As one simply has to hold something to have his/her tremor recorded, the acquisition process is not invasive. Thus, our opinion is that tremor should have high acceptability and we foresee this aspect will be one of the key feature that will lead to its development as a biometric measure.

Circumvention. Unfortunately, here we will count a weak point. The development of piezoelectric transducer is at a level high enough, so that one will easily program such a device to mimic another's tremor characteristics. We may only hope that in the development process of the tremor as a biometric other features of the tremor, hard to be replicated, will be identified.

5.2. Applications

Typically, the biometric systems operate in either verification mode or identification mode. In this paper we focused on the identification mode, reporting an average accuracy of 76% and only performed a side test for verification, which produced an accuracy of 98%. However, we must point out that the test for verification is only partially relevant as we tested the system only with persons that were included in the training database. A completely relevant test for verification should contain more persons in training and test on the tremor of completely new people.

Regarding practical applications, the most intuitive one is currently under development by us and it is smartphone unlocking based on tremor. Given a trained system, after slightly more than one second of holding, we are capable of reporting a result about holder's identity. This is faster, less intrusive and less demanding than any PIN code introduction, swipe unlocking or face recognition through front camera image processing.

Supplementary we anticipate that given initial person identification, afterwards the smartphone can be customized to user preferences.

5.3. Conclusion and future work

Given the achieved performance of the random forests classifier the person recognition based on tremor characteristics is indeed viable. Complementary, the hand tremor meets all the criteria for a biometric measure. Thus the physiological tremor recognition can become a major security improvement for smartphones with the added benefit that no additional hardware is needed.

To fully understand the tremor potential and limits as a biometric measure, significant additional work is needed, spanning from larger database to trying other features for description and different systems for classification.

Given the discrimination power amongst different persons, we consider that it is worthy to investigate if the tremor may give indication about an unknown person's age, emotional state, grip (and, consequently, posture); each of these suppositions, if validated, may end in a plethora of practical applications. Furthermore, a tremor recognition system is easy to integrate not only into a smartphone, but also into a smartwatch, a digital professional camera or it may be used in automotive industry (as a initial security step).

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